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AN EVALUATION OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM & ANN ALGORITHM PERFORMANCE FOR MPPT IN SOLAR PV SYSTEMS

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Abstract- This study presents the development and performance analysis of an Adaptive Neuro-Fuzzy Inference System (ANFIS) based Maximum Power Point Tracking (MPPT) controller for a DC-to-DC converter within a 2.0 kW PV array system. Additionally, it explores the deployment of Artificial Neural Network (ANN) based algorithms, including Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG), for MPPT energy harvesting in solar photovoltaic (PV) systems. The research aims to provide a comparative performance analysis of these four algorithms. A comprehensive comparison among the algorithms is conducted, focusing on their ability to handle the trained dataset, correlation between input-output, and error analysis. The study reveals that, considering the dataset training and the correlation between input-output and error, the Levenberg-Marquardt ANFIS algorithm exhibits superior performance among the tested algorithms. The MATLAB/Simulink environment is employed for designing the MPPT energy harvesting system, while the Artificial Neural Network toolbox is utilized for analyzing the developed model.

Keywords: ANFIS, ANN, BR, SCG, MPPT, DC to DC boost converter.

1. INTRODUCTION

Renewable energy sources (RES) are increasingly relied upon due to their clean energy generation capabilities compared to conventional sources. Among these, Photovoltaic (PV) energy sources are gaining popularity, driven by concerns over fossil fuel depletion, global warming, greenhouse gas emissions, and environmental pollution. AI-based models offer a significant advantage in rapidly approximating the Maximum Power Point (MPP) based on PV panel parameters. Artificial Neural Networks (ANN) play a pivotal role in AI, eliminating the need to solve complex mathematical relationships between output power, solar irradiance, and temperature in PV systems. Solar PV energy is an essential component of renewable energy networks, with decreasing module prices and increasing efficiency. National economies are investing heavily in both off-grid and grid-connected PV systems. However, PV electricity production is subject to variability due to factors such as solar irradiation, temperature, humidity, precipitation, wind direction, and cloud coverage. This variability poses challenges for large-scale grid-connected solar PV plants, including device flexibility, efficiency, and energy balance issues.

Accurate solar energy production forecasting is crucial for ensuring reliable energy supply. Predictive models help minimize the impact of solar PV performance variations, enhance device reliability, and reduce maintenance costs. Various Maximum Power Point Tracking (MPPT) techniques have been developed to optimize PV device performance. These include Perturb and Observe (P&O), Incremental Conductance (INC), Fuzzy Logic Controller (FLC), P&O with Particle Swarm Optimization (PSO), and Artificial Neural Networks (ANN). In this paper, Adaptive Neuro-Fuzzy Inference System (ANFIS) and ANN-based algorithms including Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG) are deployed for MPPT energy harvesting in solar PV systems. Comparative performance analysis of these algorithms reveals that ANFIS outperforms ANN-based controllers, offering greater efficiency in tracking MPP, shorter settling time, improved accuracy, and faster response, thereby enhancing system effectiveness.

2. PV SYSTEM MODEL

The PV module comprises interconnected solar cells, arranged in series and parallel configurations, and mounted on a single panel. The Single Diode Model is commonly employed to characterize PV cells, facilitating the calculation of output power through the current-voltage relationship. This relationship relies on the electrical characteristics of the model. The equivalent circuit of the Single Diode Model is depicted in Figure 2.1.

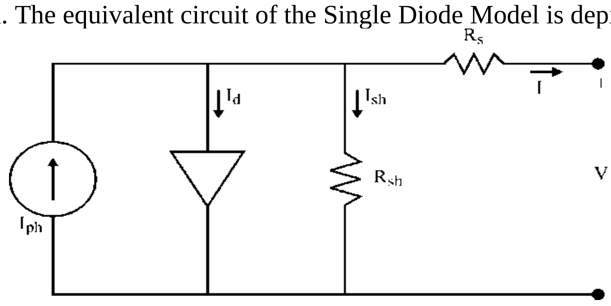

Fig. 2.1 Equivalent Circuit of Solar PV Cell

The voltage-current relationship can be written as:

$$I = I_L - I_D = I_L - I_s\left\{e\frac{q(V+\mathrm{Re})}{AKT} - 1\right\} - \frac{V+IR_e}{R_{sh}} \tag{2.1}$$

It is possible to enumerate I_L:

$$I_L = \frac{\phi}{\phi_{ref}}\left[I_{L,ref} + \mu_{sc}\left(T_C - T_{c,ref}\right)\right] \tag{2.2}$$

Saturation current I_s can be expressed at the reference condition as:

$$I_s = I_{C,ref}\left(\frac{T_{C,ref}+273}{T_C+273}\right)^3 \exp\left[\frac{e_{gap}N_S}{q_{ref}}\left(1-\frac{T_{C,ref}+273}{T_C+273}\right)\right] \tag{2.3}$$

$I_{s,rf}$ can be expressed as:

$$I_{s,ref} = I_{L,ref}\exp\left(-\frac{V_{oc,ref}}{\alpha_{ref}}\right) \tag{2.4}$$

The value of open circuit voltage at reference condition is given by manufacturer.
Value of α_{ref} can be calculated by:

$$\alpha_{ref} = \frac{2V_{mpp,ref} - V_{oc,ref}}{\frac{I_{sc,ref}}{I_{sc,ref}-I_{mpp,ref}} + In\left(1-\frac{I_{mpp,ref}}{I_{sc,ref}}\right)} \tag{2.5}$$

α is a function of temperature. The value of α can be calculated by following equation:

$$\alpha = \frac{T_c+273}{T_{c,ref}+273}\alpha_{ref} \tag{2.6}$$

The value of series resistance is provided by some manufacturers. To estimate the value of R_s following equation can be used:

$$R_s = \frac{\alpha_{ref} In\left(\frac{I_{mpp,ref}}{I_{sc,ref}-I_{mpp,ref}}\right) + V_{oc,ref} - V_{mpp,ref}}{I_{mpp,ref}} \tag{2.7}$$

After the study of the PV module, it can be said that the temperature plays an important role in the performance of PV module. It is necessary to design a thermal module for the PV system as temperature is major aspect to be considered. Temperature of PV module varies when there is a change in irradiance, its output current and voltage, and the equation can be expressed as:

$$C_{pv}\frac{dT_c}{dt} = k_{a,PV}\phi - \frac{VI}{A} - k_{loss}(T_c - T_a) \tag{2.8}$$

3. ANFIS BASED MPPT CONTROLLER

In the proposed system, interconnection is established through the DC-DC converter, which regulates the DC power output of the Solar PV array. This setup involves the direct connection of the solar array to the DC-DC boost converter, with the converter then linked to the load R. The ANFIS based MPPT controller utilizes the PV voltage and current as inputs and outputs the duty ratio for the PWM controller, operating at a switching frequency of 4kHz. Figure 3.1 depicts a simple block diagram of a DC-DC converter for Solar Energy Conversion Systems (SECS) employing an Adaptive Neuro-Fuzzy Inference System (ANFIS) based Maximum Power Point Tracking (MPPT) Controller. The proposed system comprises a PV array, power electronics interfacing devices such as a DC-DC Boost converter, load arrangement, and the ANFIS based MPPT Controller. To enhance the performance of maximum power point tracking in solar PV systems, an efficient ANFIS based MPPT Controller is developed and compared with conventional ANN based MPPT controllers.

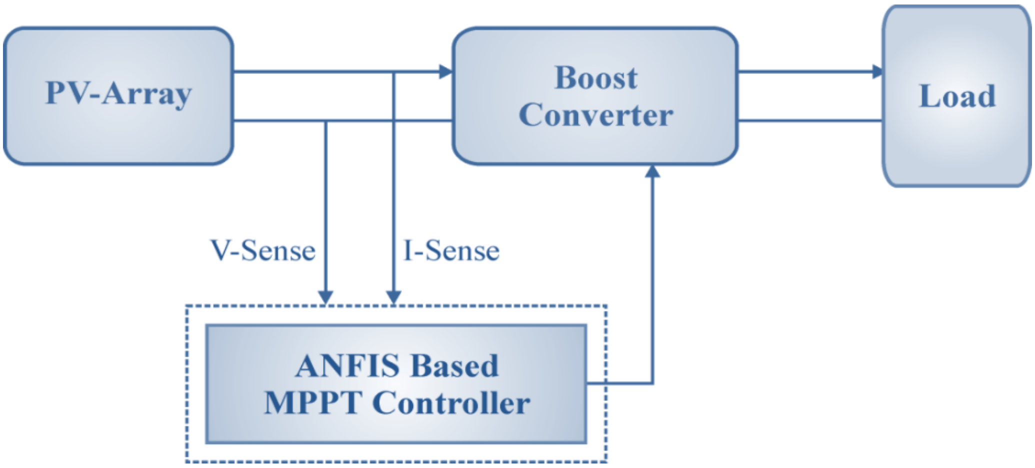

Fig. 3.1 Block Diagram of DC-DC Converter for SECS using ANFIS based MPPT Controller

In essence, parallel distributed models, such as Artificial Neural Networks (ANNs), possess the potential to conduct non-linear modeling and adaptation without relying on any predefined assumptions about the model. At a high level, ANNs can be described as an endeavor to replicate the problem-solving capabilities of the human brain.

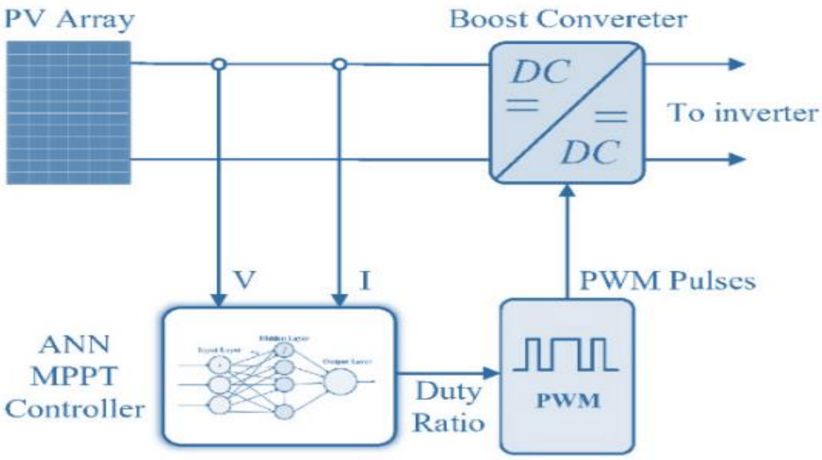

Fig. 3.2 Block Diagram of ANN MPPT Controller

The ANN comprises multiple artificial neurons interconnected via variable-weight connections. Its basic architecture typically includes three layers: an input layer, a hidden layer, and an output layer. In the context of a PV system, the neural network features two input variables—voltage and current. The hidden layer is composed of 15 neurons.

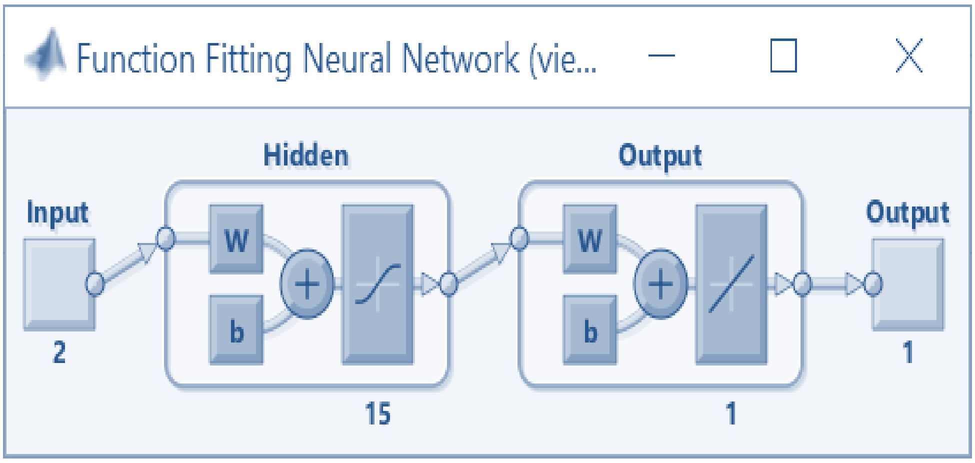

Fig. 3.3 Architecture of Levenberg-Marquardt ANN

The Levenberg-Marquardt algorithm is employed to train the neural network for the Maximum Power Point Trackers (MPPTs). Figure 3.3 illustrates the block diagram of the MPPT controller scheme, while Figure 3.4 depicts the developed block diagram of the ANN algorithm.

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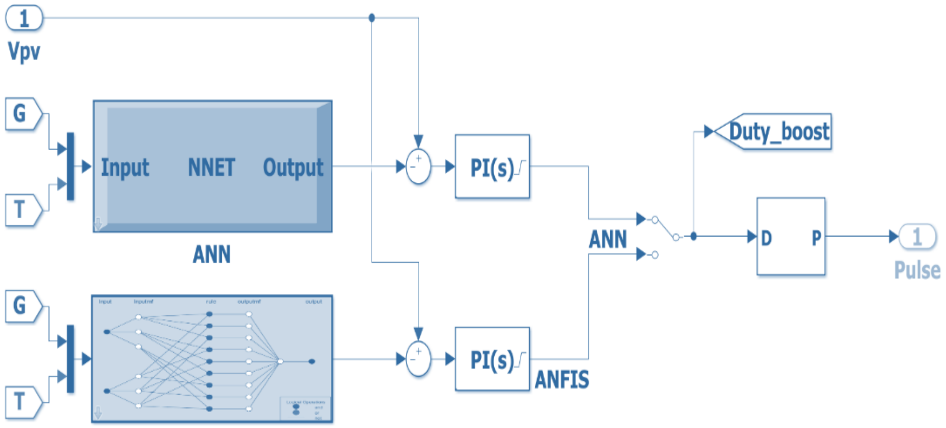

Fig. 3.4 The developed block of ANN algorithm

4. SIMULATION RESULT FOR EVALUATION OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM & ANN ALGORITHM PERFORMANCE FOR MPPT IN SOLAR PV SYSTEMS

Case-1: Simulation results at step-changes irradiance from 600 w/m^2 to 1000 w/m^2 & constant temperature of 25°C.

In this scenario, the irradiance undergoes step changes from 600 W/m^2 to 1000 W/m^2 during two time intervals: from t=0 to t=3 seconds and from t=3 to t=6 seconds, respectively. Throughout the entire simulation period, the temperature and load remain constant. The simulation results are depicted in the following figures. Figure 4.1 displays the waveforms of irradiance and temperature applied at the input of the PV panel.

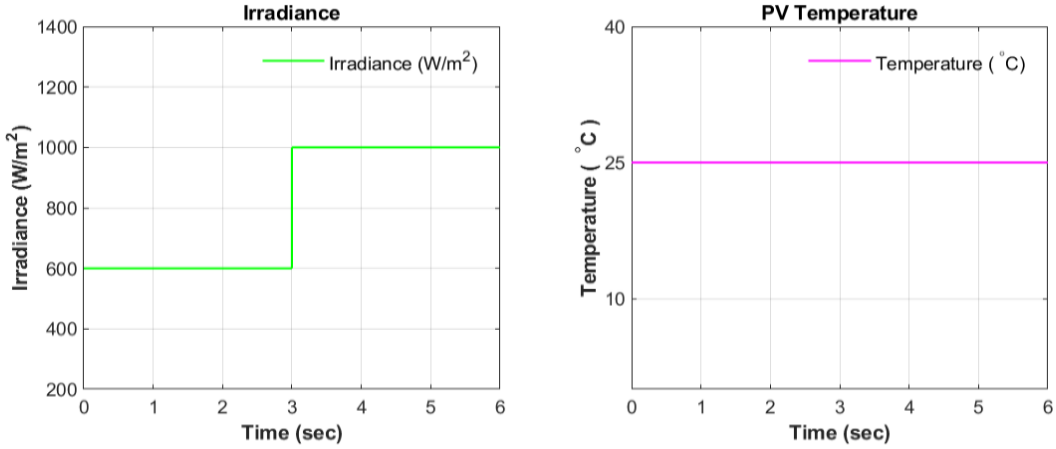

Fig. 4.1 Simulation Results at Step-changes Irradiance from 600 w/m2 to 1000 w/m2 & Constant Temperature of 25°C, Respectively, Waveform of Irradiance and Temperature

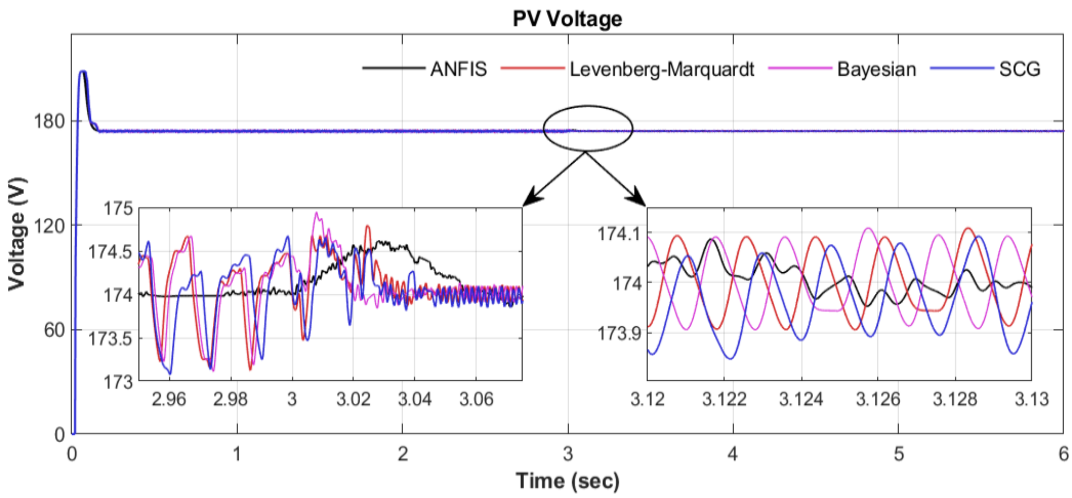

Fig. 4.2 Simulation Results at Step-changes Irradiance from 600 w/m2 to 1000 w/m2 & Constant Temperature of 25°C, respectively, Waveform of PV Voltage

Figure 4.2 illustrates the waveform of the PV array voltage. Throughout the simulation period, the PV voltage remains approximately constant at around 174V. Additionally, two zoomed subplot windows are provided to highlight the differences among the Levenberg-Marquardt neural network, Bayesian Regularization network, Scaled Conjugate Gradient network, and ANFIS network for MPPT algorithms.

In the first window, the response of the algorithms is observed when the irradiance changes from 600 W/m2 to 1000 W/m2 at time t=3 seconds. At an irradiance of 600 W/m2, the PV voltage is approximately 174V for the ANFIS algorithm, while for the other neural network algorithms, it ranges between 173V and 175V.

The second window displays the response at 1000 W/m2 between the time interval of t=3.12 seconds to t=3.13 seconds.

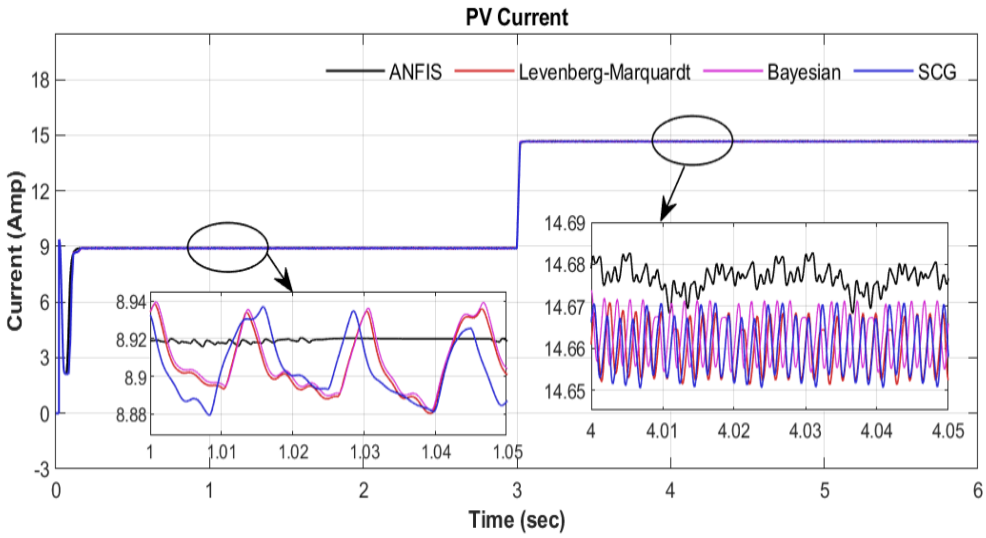

Fig. 4.3 Simulation Results at Step-changes Irradiance from 600 w/m^2 to 1000 w/m^2 & Constant Temperature of 25°C, Respectively, Waveform of PV Current

Figure 4.3 displays the waveform of the PV current generated by the PV array. Two zoomed subplot windows are provided to illustrate the differences among the Levenberg-Marquardt neural network, Bayesian Regularization network, Scaled Conjugate Gradient network, and ANFIS network for MPPT algorithms.

In the first window, the discrepancy in PV current at 600 W/m2 is observed among the algorithms between the time interval of t=1 second to 1.05 seconds. The PV current generated by the ANFIS algorithm is approximately 8.92A, while for the Levenberg-Marquardt neural network and Bayesian Regularization network, it ranges between 8.9A and 8.935A, and for the SCG network, it ranges between 8.88A and 8.94A.

The second window spans the time interval of t=4 seconds to 4.05 seconds, where the PV current due to the neural network algorithms ranges between 14.65A and 14.67A, whereas the PV current due to the ANFIS algorithm is approximately 14.68A.

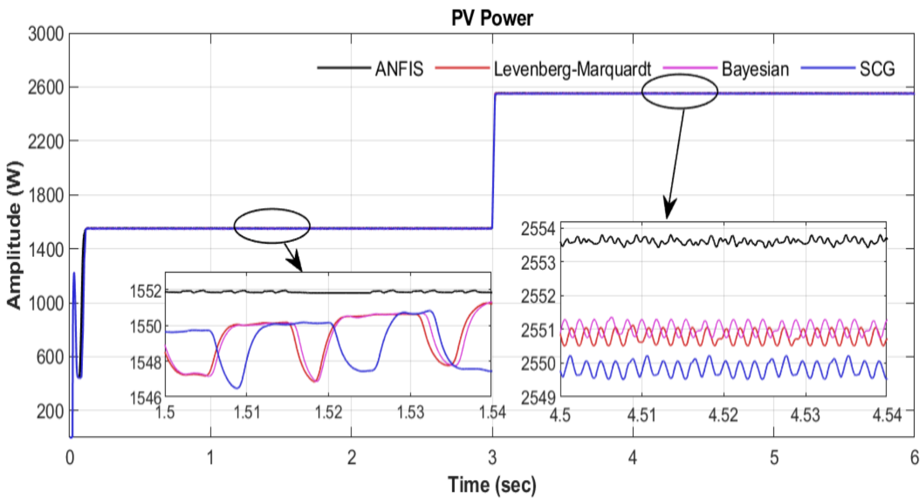

Fig. 4.4 Simulation Results at Step-change Irradiance from 600 w/m2 to 1000 w/m2 & Constant Temperature of 25°C, Respectively, Waveform of PV Output Power

Figure 4.4 depicts the waveform of the PV output power. Two zoomed subplot windows are included to demonstrate the differences in PV output power between the ANFIS algorithm and other neural network algorithms.

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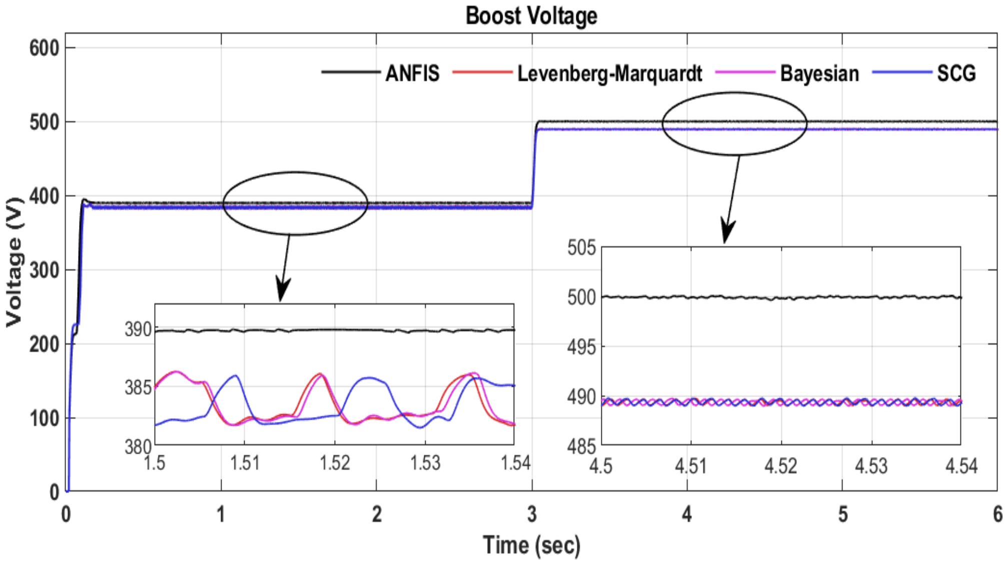
In the first window, spanning the time interval of t=1.5 seconds to 1.54 seconds, the PV power at 600 W/m2 irradiance is approximately 1552W for the ANFIS algorithm, while for other neural network algorithms, it is around 1549W.

The second window covers the time interval of t=4.5 seconds to 4.54 seconds. At an irradiance of 1000 W/m2, the PV power is approximately 2554W for the ANFIS algorithm, 2551W for the Levenberg-Marquardt and Bayesian Regularization neural network algorithms, and 2550W for the Scaled Conjugate Gradient network algorithm.



(a)

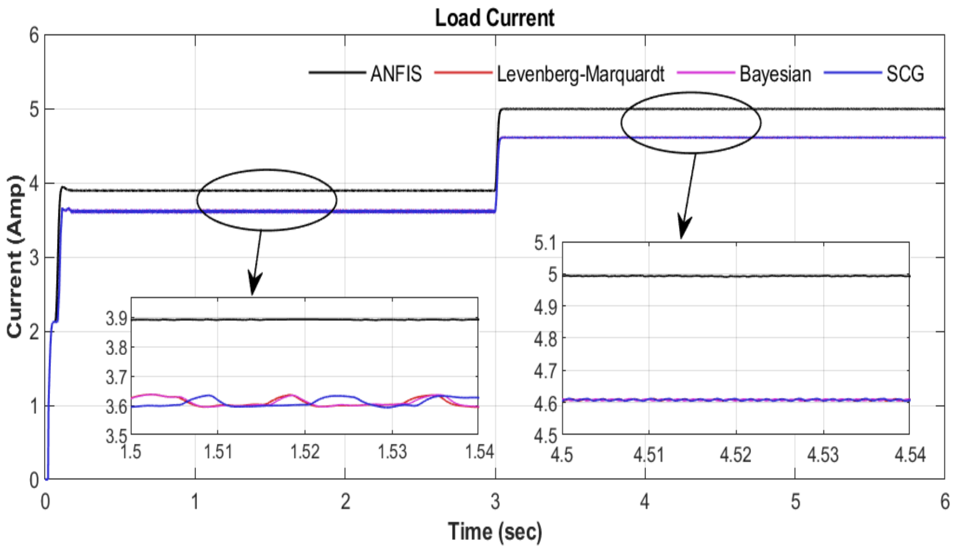


Fig. 4.5 Simulation results at step-change irradiance from 600 w/m2 to 1000 w/m2 & constant temperature of 25°C, respectively, Waveform of (a) boost converter output voltage and, (b) load current

Figure 4.5 (a) and (b) display the boost converter output voltage and load current, respectively. Two zoomed windows are provided, spanning the time intervals of t=1.5 seconds to 1.54 seconds and t=4.5 seconds to t=4.54 seconds.

In Figure 4.5 (a), at an irradiance of 600 W/m^2, the boost converter output voltage is approximately 390V for the ANFIS algorithm and between 380V and 385V for other neural network algorithms during the time interval of t=1.5 seconds to 1.54 seconds, as shown in the first window. At an irradiance of 1000 W/m^2, the boost converter output voltage is approximately 500V for the ANFIS algorithm and nearly 490V for other neural network algorithms during the time interval of t=4.5 seconds to 4.54 seconds, as shown in the second window.

In Figure 4.5 (b), at an irradiance of 600 W/m^2, the load current is approximately 3.9A for the ANFIS algorithm and between 3.6A and 3.65A for other neural network algorithms during the time interval of t=1.5 seconds to 1.54 seconds, as shown in the first window. At an irradiance of 1000 W/m^2, the load current is approximately 5A for the ANFIS algorithm and around 4.6A for other neural network algorithms during the time interval of t=4.5 seconds to 4.54 seconds, as shown in the second window. Fig. 4.6 shows, the waveform of comparison of MPPT algorithms for generating boost converter duty cycle.

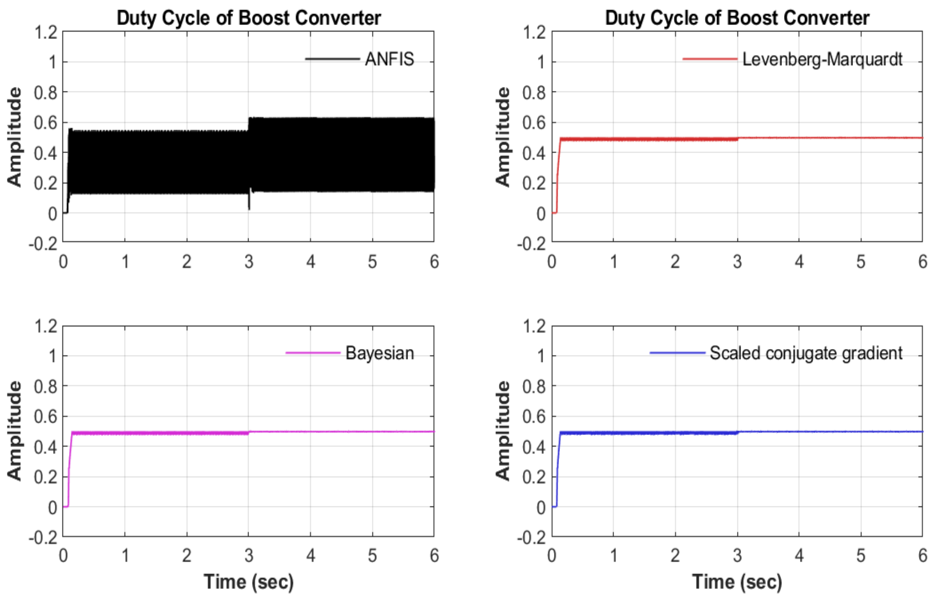


Fig. 4.6 Simulation Results at Step-change Irradiance from 600 w/m2 to 1000 w/m2 & Constant Temperature of 25°C, Respectively, Waveform of Boost Converter Duty Cycle

CONCLUSION

This paper introduces a standalone solar energy conversion system featuring a DC-DC converter equipped with a Maximum Power Point Tracking (MPPT) technique, leveraging an ANFIS (Adaptive-Network-Based Fuzzy Inference System) based MPPT Controller to optimize power output. A novel comparative analysis is proposed, evaluating the performance of three ANN algorithms—Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient—for MPPT energy harvesting in solar PV systems. The ANN toolbox employs a two-layer feedforward neural network, trained with real-time input datasets of solar irradiance and panel temperature, alongside output datasets of generated voltage. Through training with 1000 datasets, the ANN algorithms are assessed to determine the most suitable approach. The ANFIS algorithm demonstrates superior performance in overall data processing, achieving near-zero error during the middle epoch. This proposed system holds potential for implementation across various solar PV systems and advanced technological applications such as space satellites, telecommunications, and military equipment. Additionally, it can be integrated into solar radiation and temperature forecasting, energy consumption prediction, energy management systems, smart homes, and smart cities.

REFERENCES

[1] S. Kouro, J. I. Leon, D. Vinnikov, and L. G. Franquelo, ''Grid-connected photovoltaic systems: An overview of recent research and emerging PV converter technology,'' IEEE Ind. Electron. Mag., vol. 9, no. 1, pp. 47–61, Mar. 2015, doi: 10.1109/MIE.2014.2376976.

[2] Md Tahmid Hussain., et. al., "An Evaluation of ANN Algorithm Performance for MPPT Energy Harvesting in Solar PV Systems," Sustainability 2023, 15(14), 11144; https://doi.org/10.3390/su151411144, 2023.

[3] Roy. R. B., et. al., "A Comparative Performance Analysis of ANN Algorithms for MPPT Energy Harvesting in Solar PV System," IEEE Access, vol. 9, no. 2, pp. 102137–102152, 2022.

[4] M. Rokonuzzaman, M. K. Mishu, N. Amin, M. Nadarajah, R. B. Roy, K. S. Rahman, A. M. Buhari, S. Binzaid, M. Shakeri, and J. Pasupuleti, ''Self-sustained autonomous wireless sensor network with integrated solar photovoltaic system for internet of smart home-building (IoSHB) applications,'' Micromachines, vol. 12, no. 6, p. 653, Jun. 2021, doi: 10.3390/mi12060653.

[5] B. Tarroja, B. Shaffer, and S. Samuelsen, ''The importance of grid integration for achievable greenhouse gas emissions reductions from alternative vehicle technologies,'' Energy, vol. 87, pp. 504–519, Jul. 2015, doi: 10.1016/j.energy.2015.05.012.

[6] M. Rokonuzzaman, M. K. Mishu, N. Amin, M. Nadarajah, R. B. Roy, K. S. Rahman, A. M. Buhari, S. Binzaid, M. Shakeri, and J. Pasupuleti, ''Self-sustained autonomous wireless sensor network with integrated solar photovoltaic system for internet of smart home-building (IoSHB) applications,'' Micromachines, vol. 12, no. 6, p. 653, Jun. 2021, doi: 10.3390/mi12060653.

[7] M. Aarif; D. Joshi; R. Jangid and S.S. Sharma, "Grid Power Smoothing Management for Direct Drive PMSG Variable Speed Wind Energy Conversion System with Multilevel Converter", IEEE 7th International Conference on ICT for Sustainable Development, Organized by Global Knowledge Foundation during 29-30, July 2022 at Goa, India.

ISSN Number: 2454-2024(Online)

International Journal of Technical Research & Science

[8] Y. Joshi; J.k Maherchandani; V.K Yadav; R. Jangid; S. Vyas and S.S Sharma, "Performance Improvement of Standalone Battery Integrated Hybrid System" IEEE 7th International Conference on Electrical Energy Systems (ICEES), Organized by Sri Sivasubramaniya Nadar College of Engineering during 11-13 Feb. 2021at Chennai, India.

[9] R. Jangid; J.k Maherchandani; R.R. Joshi and B.D Vairagi, "Development of Advance Energy Management Strategy for Standalone Hybrid Wind & PV System Considering Rural Application", IEEE 2nd International Conference on Smart Systems and Inventive Technology, Organized by Francis Xavier Engineering College during November 27-29, 2019 at Tirunelveli, India.

[10] R. Jangid; K. Parikh and P. Anjana, "Reducing the Voltage Sag and Swell Problem in Distribution System Using Dynamic Voltage Restorer with PI Controller", International Journal of Soft Computing and Engineering, ISSN: 2231-2307, Vol.-3, Issue-6, January 2014.

[11] R. Jangid; J.k Maherchandani; V.K Yadav and R.K Swami, "Energy Management of Standalone Hybrid Wind-PV System", Journal of Intelligent Renewable Energy Systems (John Wiley & Sons, Inc.) Pages 179-198, 2022.

[12] H. Kumawat and R. Jangid, "Using AI Techniques to Improve the Power Quality of Standalone Hybrid Renewable Energy Systems", Crafting a Sustainable Future Through Education and Sustainable Development, IGI Global, Pages 219-228, 2023.

[13] H. Kumawat; R. Jangid, "Performance and Investigation of Two Drive Train Interfaced Permanent Magnet Synchronous Generator for Wind Energy Conversion System", Journal of Emerging Technologies and Innovative Research, ISSN:2349-5162, Volume 7, Issue 1, January 2020.

[14] R. Jangid et. al., "Smart Household Demand Response Scheduling with Renewable Energy Resources", IEEE Third International Conference on Intelligent Computing and Control System, Organized by Vaigai College of Engineering during May 15-17, 2019 at Madurai, India.

[15] S. Kumar; R. Jangid and K. Parikh "Comparative Performance Analysis of Adaptive Neuro-Fuzzy Inference System (ANFIS) & ANN Algorithms Based MPPT Energy Harvesting in Solar PV System." International Journal of Technical Research and Science, vol. 8, Issue 3, March 2023.

[16] S. Sharma; R. Jangid and K. Parikh "Development of Intelligent Control Strategy for Power Quality Improvement of Hybrid RES Using AI Technique" International Journal of Technical Research and Science, vol. VIII, Issue II, Feb. 2023.

[17] L. Jhala et al., "Development of Control Strategy for Power Management in Hybrid Renewable Energy System" International Journal of Technical Research and Science, vol. VI, Issue XII, Dec. 2021.

[18] S. Koohi-Kamali, N. A. Rahim, H. Mokhlis, and V. V. Tyagi, ''Photovoltaic electricity generator dynamic modeling methods for smart grid applications: A review,'' Renew. Sustain. Energy Rev., vol. 57, pp. 131–172, May 2016, doi: 10.1016/j.rser.2015.12.137.

[19] M. G. De Giorgi, P. M. Congedo, and M. Malvoni, ''Photovoltaic power forecasting using statistical methods: Impact of weather data,'' IET Sci. Meas. Technol., vol. 8, no. 3, pp. 90–97, May 2014, doi: 10.1049/ iet-smt.2013.0135.

[20] N. Karami, N. Moubayed, and R. Outbib, ''General review and classification of different MPPT techniques,'' Renew. Sustain. Energy Rev., vol. 68, pp. 1–18, Feb. 2017, doi: 10.1016/j.rser.2016.09.132.

[21] M. K. Mishu, M. Rokonuzzaman, J. Pasupuleti, M. Shakeri, K. S. Rahman, F. A. Hamid, S. K. Tiong, and N. Amin, ''Prospective efficient ambient energy harvesting sources for IoT-equipped sensor applications,'' Electronics, vol. 9, no. 9, p. 1345, Aug. 2020, doi: 10.3390/electronics9091345.

[22] M. Rokonuzzaman, M. Shakeri, F. A. Hamid, M. K. Mishu, J. Pasupuleti, K. S. Rahman, S. K. Tiong, and N. Amin, ''IoT-enabled high efficiency smart solar charge controller with maximum power point tracking—Design, hardware implementation and performance testing,'' Electronics, vol. 9, no. 8, p. 1267, Aug. 2020, doi: 10.3390/electronics9081267.

[23] P. Sivakumar, A. A. Kader, Y. Kaliavaradhan, and M. Arutchelvi, ''Analysis and enhancement of PV efficiency with incremental conductance MPPT technique under non-linear loading conditions,'' Renew. Energy, vol. 81, pp. 543–550, Sep. 2015.

[24] R. B. Roy, E. Basher, R. Yasmin, and M. Rokonuzzaman, ''Fuzzy logic based MPPT approach in a grid connected photovoltaic system,'' in Proc. 8th Int. Conf. Softw., Knowl., Inf. Manage. Appl. (SKIMA), Dec. 2014, vol. 1, no. 1, pp. 1–6, doi: 10.1109/SKIMA.2014. 7083525.

[25] A. R. Bhatti, Z. Salam, B. Sultana, N. Rasheed, A. B. Awan, U. Sultana, and M. Younas, ''Optimized sizing of photovoltaic grid-connected electric vehicle charging system using particle swarm optimization,'' Int. J. Energy Res., vol. 43, no. 1, pp. 500–522, Jan. 2019, doi: 10.1002/er.4287.

[26] T. V. Dixit, A. Yadav, and S. Gupta, ''Experimental assessment of maximum power extraction from solar panel with different converter topologies,'' Int. Trans. Electr. Energy Syst., vol. 29, no. 2, pp. 1–33, Feb. 2019, doi: 10.1002/etep.2712.

[27] M. Rokonuzzaman and M. Hossam-E-Haider, ''Design and implementation of maximum power point tracking solar charge controller,'' in Proc. 3rd Int. Conf. Electr. Eng. Inf. Commun. Technol. (ICEEICT), Sep. 2016, pp. 1–3, doi: 10.1109/CEEICT.2016.7873139.

[28] Rajib Baran Roy et al., "A Comparative Performance Analysis of ANN Algorithms for MPPT Energy Harvesting in Solar PV System," Elsevier Renewable and Sustainable Reviews,Vol. 13, October 2009, pp.2096-2103.

[29] Nema, P; Nema, R.K and Rangnekar, S. "A Current and Future state of art development of Hybrid Energy system using Wind and PV Solar," IEEE Access,Vol. 9, 2021, pp.102137-102152.

[30] Sassi, A., Zaidi, N., Nasri, O and Slama, J.B.H. 2017. Energy management of PV/wind/battery hybrid energy system based on batteries utilization optimization, IEEE International Conference on Green Energy Conversion Systems held at Tunisia during Mar. 23-25, 2017, pp. 1-7.

[31] Rehman, S; Alam, MD.M; Meyer, J.P and Al-Hadhrami, L.M. " Feasibility study of a wind-pv-diesel hybrid power system for a village," Elsevier Renewable Energy, vol. 38, Febuary 2012, pp.258- 268.

[32] Khan, B.H "Non-Conventional Energy Resources," Tata McGraw-Hill Pub.Co., 2009.

[33] Dali, M., Belhadj, J., Roboam, X.: 'Hybrid solar-wind system with battery storage operating in grid–connected and standalone mode: Control and energy management-experimental investigation', Energy, 2010, 35, pp. 2587–2595.

[34] Nguyen, X. H. and Nguyen, M. P. 2015. Mathematical modeling of photovoltaic cell/module/arrays with tags in Matlab/Simulink, Environmental Systems Research.4(1):1-13.

[35] Kamal, T., Karabacak, M., Hassan, S. Z., Li, H., Arsalan, A., & Rajkumar, R. K. 2017. Integration and control of an off-grid hybrid wind/PV generation system for rural applications. International Conference on Innovations in Electrical Engineering and Computational Technologies held at Karachi, during 5-7 April 2017, pp. 1-6.

[36] Priyadarshi, N., Padmanaban, S., Ionel, D. M., Popa, L. M. and Azam, F., "Hybrid PV-Wind, micro-grid development using quasi-z-source inverter modeling and control-experimental investigation," Energies, vol. 11, pp.1-15, 2018.

[37] Zeng, J., Ning, J., Du, X., Kim, T., Yang, Z. and Winstead, V., "A four-port DC-DC converter for a standalone wind and solar energy system," IEEE Transactions on Industry Applications, vol. 56, pp. 446-454, 2020.

[38] Khateb, A. H. E., Rahim, N. A., Selvaraj, J. and Williams, B. W., "DC-to-DC converter with low input current ripple for maximum photovoltaic power extraction," IEEE Transactions on Industrial Electronics, vol. 62, pp. 2246-2256, 2015.

[39] Ahmadi, M. and Shenai, K., "New, efficient, low-stress buck/boost bidirectional DC-DC converter," In: Proceedings of IEEE Energy tech conference held at Cleveland during May 29-31, 2012, pp. 1-6.

[40] Wandhare, R.G. and Agarwal, V., "Novel integration of PV-Wind energy system with enhanced efficiency," IEEE Transactions on Power Electronics, vol. 30, pp. 3638-3649, 2015.

[41] Sharma, A. and Jamuna, K., "Coordination of energy storage devices in hybrid power systems," In: Proceedings of Springer International conference on Emerging Trends in Electrical, Communications and Information Technologiesheld at India during November 15-16, 2016, pp. 327-336.

[42] Manandhar, U., Tummuru, N. R. and Kollimalla, S. K., "Validation of faster joint control strategy for battery- and super capacitor-based energy storage system," IEEE Transactions on Industrial Electronics, vol. 65, pp. 3286-3295, 2018.

[43] Lei, M., Yang, Z., Wang, Y., and Honghua, X., "Design of energy storage control strategy to improve the PV system power quality," In: Proceedings of IEEE 42nd Annual Conference of the Industrial Electronics Society (IECON) held at Italy during October 23-26, 2016, pp. 2022-2027.

[44] Faria, J., Pombo, J., Calado, M. and Mariano, S., "Power management control strategy based on artificial neural networks for standalone PV applications with a hybrid energy storage system," Energies, vol. 12, no.2, pp. 1-24, 2019.